APEM journal

Advances in Production Engineering & Management
Volume 15 | Number 2 | June 2020 | pp 137–150
https://doi.org/10.14743/apem2020.2.354

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Comparison of artificial neural network, fuzzy logic and genetic algorithm for cutting temperature and surface roughness prediction during the face milling process

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ABSTRACT

This paper shows the possibility of applying artificial intelligence methods in milling, as one of the most common machining operations. The main goal of the research is to obtain reliable intelligent models for selected output characteristics of the milling process, depending on the input parameters of the process: depth of cut, cutting speed and feed to the tooth. One of the problems is certainly determining the value of input parameters of the processing process depending on the objective function, i.e. the output characteristics of the milling process. The selected objective functions in this paper are the temperature in the cutting zone and arithmetic mean roughness of the machined surface. The paper examines the accuracy of three models based on artificial intelligence, obtained through artificial neural networks, fuzzy logic, and genetic algorithms. Based on the mean percentage error of deviation, conclusions were drawn as to which of the three models is most adequately applied and implemented in appropriate process systems, which are based on artificial intelligence.

ARTICLE INFO

Keywords:
Artificial intelligence;
Artificial neural networks (ANN);
Fuzzy logic (FL);
Genetic algorithms (GA);
Face milling;
Modeling;
Surface roughness;
Cutting temperature

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Article history:
Received 14 June 2019
Revised 20 June 2020
Accepted 23 June 2020

1. Introduction

There is a need to improve the machining process by applying knowledge from advanced modeling techniques, such as simulation, which certainly involves modeling using artificial intelligence methods. The developed models are used for the analysis, management and selection of optimal process parameters, which represent a picture of complex relationships between the input and output parameters of the milling process. The obtained models can be used with sufficient accuracy in adaptive management and monitoring of processes and decision making in real time, which is of great importance in the exploitation of intelligent manufacturing systems. It is also possible to optimize the input process parameters based on the processing constraints set in order to achieve one or more target functions such as reducing cutting forces and/or minimizing the roughness of the machined surface, which have the greatest practical value and meaning from a technical point of view. In terms of quality of the machined surface, the emphasis on the roughness test as well as the influence of the corresponding parameters was given by a large number of authors [1-4].

Applying methods and techniques of artificial intelligence together with modeling, simulation and optimization of production processes lead to the generation of new and better solutions during manufacturing [5-8]. Their application leads to the development of intelligent processing systems that automatically perform complex production problems, freeing people not only from physical but also intellectual work, leaving them to do expert and creative jobs.

Artificial intelligence can be considered an experimental doctrine where experiments are performed on a computer within the models that are expressed in programs and whose testing and upgrading achieve some models of human intelligence. By algorithm it is usually meant a finite set of precisely defined operations that can be performed on a computer. One of the areas of artificial intelligence, together with its sub-areas, is computer intelligence *(soft computing).* It is a basic artificial intelligence tool that involves series of methods and techniques for the conception, design and use of an intelligent system. As such, the tool is certainly attractive for creating various models that describe certain phenomena in the production process.

The objective of this paper is to determine the optimal model obtained on the basis of artificial intelligence for predicting the roughness of the machined surface, i.e. the temperature in the cutting zone during of the face milling process. The proposed models are realized as a function of processing parameters: cutting speed, feed per tooth and cutting depth. The most common artificial intelligence methods are surely: fuzzy logic, artificial neural networks and genetic algorithms. Accordingly, it is necessary to determine which of these three types for model creation most closely describes the change in the output characteristics of the process.

2. Literature review

Artificial neural networks (ANN) are nowadays used in almost all fields of science and technology, including mechanical engineering. Technological processing parameters are values that depend on a large number of factors. There are no exact forms and procedures for determining processing parameters, so in most cases, experience values are used, like various books, tables, graphics, etc. Therefore, neural networks can be of great use. Instead of a detailed calculation of the processing parameters, a neural network is created that can predict the unknown machining parameters, after a properly training process [9]. Today, artificial neural networks are widely used in the industrial sector to solve problems [10-12].

An example of the implementation of ANN can be seen in the paper [13]. The application of neural networks for the calculation of cutting force, torque and monitoring of tool wear during the drilling process is presented there. Also, these principles of neural networks application can be seen in other kinds of cutting material process. This primarily refers to the milling process as one of the most common cutting process [14]. There are papers showing the application of the network structure in the milling process for variables such as tool geometry and machining regimes [15].

In their research, Lin and Liu present the methodology of creating the neural network structure, emphasizing the type of function as well as the number of hidden layers in the network itself. It should be pointed out that it is very important which type of neural network, i.e. the number of nodes in individual layers, is the most appropriate to choose and to obtain a sufficiently reliable model. Based on the analysis of the papers [16, 17], it can be concluded that the back-propagation neural network is sufficiently reliable. Also, it was noticed that the faster convergence is achieved using a two-hidden-layer network than using a one-hidden-layer network, with the same number of nodes.

The neural networks application is also present in the adaptive control of the spindle milling process [18]. ANN are used for on-line determination of optimal milling parameters, specifically feed per tooth, based on the values of measured cutting forces.

Next, a certainly not less important tool of artificial intelligence is Fuzzy logic. It represents the generalization of the classical Boolean logic. Systems based on fuzzy logic and fuzzy sets can be observed as a generalization of expert systems based on rules. Fuzzy systems manifest both symbolic and numerical features.

It can also be said that fuzzy logic and fuzzy systems represent an effective techniques to identify and control complex non-linear systems. Fuzzy logic is also used for prediction. The theory of fuzzy logic, which has been initiated Zadeh [19], is still helpful for the operation with uncertain and inaccurate information. Fuzzy logic is especially attractive because of its ability to solve problems in the absence of precise mathematical models. This theory has proved to be an effective tool for describing objectives expressed through linguistic terms, such as *small*, *medium* and *high*, which may be defined as the fuzzy sets [20].

Application of fuzzy logic to solve problems in the cutting process is very common and it can be seen through the overview of following papers. Rajasekaran *et al*. [21] investigated the influence of combinations of processing parameters in order to obtain a good quality when finishing machining by turning. They used the fuzzy modeling to predict the value of surface roughness. Other literature sources also show the application of the adaptive approach based on the network of fuzzy logic system (ANFIS), set to show the correlation of surface roughness when machining by turning or milling [22, 23]. The implementation of fuzzy logic in surface roughness modeling when finishing machining has also been discussed in paper [24]. It can be stated that the fuzzy logic is a recognizable system, sufficiently developed and widely used [25].

Surface roughness modelling when face milling is considered a complex process. The concept of fuzzy reasoning for four inputs and one output fuzzy logic unit (singleton) is excellently presented in [26]. Cutting speed, feed per tooth, cutting depth and flank wear were set as input variables, while the output variable was the roughness of the machined surface.

Similar issues were described by the authors in paper [27], where the cutting speed, feed per tooth, cutting depth and flank wear were taken as input parameters as well, but this time the output variables were tool life and cutting temperature.

At the end of this review of artificial intelligence application, it is necessary to analyze genetic algorithms (GA). Genetic algorithms are an effective way to quickly find a solution to a complex problem. They are certainly not fast but they do a great job of searching large areas. They are also most effective when searching an area which is very little known or not known at all. Terminology and operators are taken from the field of population genetics. The basic object of genetic algorithms is the chromosome, and they represent an instantaneous approximation of the solution for the set goal function. Each chromosome is encoded and has a certain quality – fitness. During initialization, the initial population is generated, which is a solution obtained by another optimization method. Then follows a repetitive process until the stop condition is met. This process consists of the execution of genetic operators of selection, crossover and mutation. By multiple application of the selection operator, mostly bad individuals become extinct, and better ones stay alive, and the next step is crossing over between the good individuals. The characteristics of parents are transferred to children by crossover operator. Mutation changes the characteristics of individuals by random change of genes. One such procedure enables the average quality of the population to grow from generation to generation. Essentially, this is a heuristic optimization method that solves certain computer problems by simulating the mechanism of natural evolution.

Accordingly, it can be stated that the mechanism on which GA is based, can be used in order to optimize or to model the value that occur in certain production processes. Thus, in addition to the wide domain of application of the genetic algorithm, they also found their implementation in designing of CNC control [28]. When it comes to artificial intelligence, specifically based on genetic algorithms, it has found its application in machining processes where material is removed. Thus, there is an example of using genetic algorithms to perform optimization of parameters in the examination of surface morphology [29]. Genetic algorithms are also used for modeling the cutting force in machining process of hard materials such as titanium alloys [30]. They have also found their application in the processing of aluminium, specifically for the optimization of processing parameters [31]. There are also papers in which the authors deal with modeling the temperature during milling with the help of GA [32].

3. Materials and methods

Conditions for predicting the appropriate machinability values are created by defining the model. Those conditions allow the technologist or CNC programmer to select the appropriate machining regimes long before the actual machining. By knowing these values of machinability, the

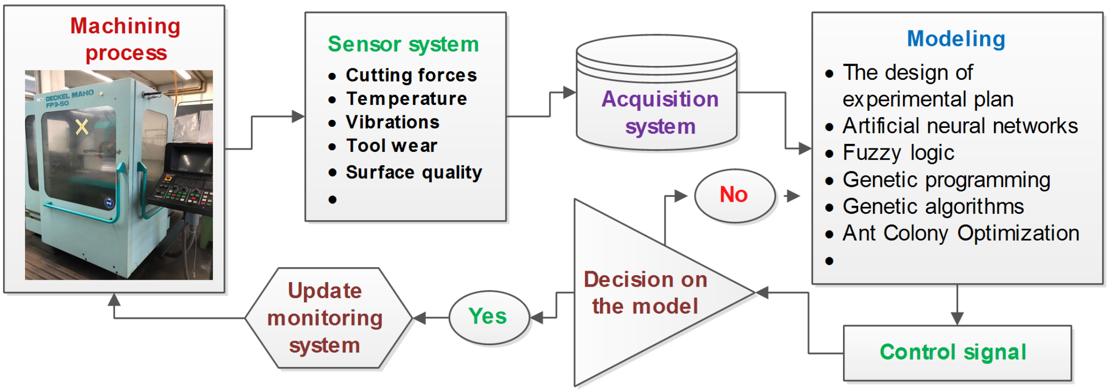

Fig. 1 Monitoring, modeling and control signal in machining process

conditions are created to achieve control of machining systems. Certainly, assuming that the best production process was previously selected in relation to the set criteria [33]. Fig. 1 shows the scheme of intelligent control and monitoring of the machining process. The figure shows that the part for modeling collected data is located at the central part of the system.

Experimental setup

The material used for workpiece was aluminum alloy. It is an alloy from 7000 series which contains a high percentage of zinc (Zn), as the main alloying element, and magnesium (Mg) as the second alloying element. Beside Zn and Mg, the alloy code 7075 also contains copper (Cu) as a fourth alloying element, i.e. it is a multicomponent Al-Zn-Mg-Cu alloy. The alloys 7075 have high mechanical properties, good machinability and heat-treated process, and also good corrosion resistance [34]. They belong to the group of *hard alloys*. They are usually used in the aviation and military industry. The forms they are usually used are: sheets, plates, wires, rods, extruded products, structural shapes, pipes, forgings etc. [35].

Fig. 2 shows the typical microstructure of the tested samples of Al 4.4 % Cu alloys obtained by conventional casting. Table 1 shows the chemical composition of the tested alloys.

The experiments was performed on a vertical milling machine FSS-GVK-3 with a face milling head diameter of ϕ100 mm, with removable inserts following characteristics: number of teeth t = 5, entrance angle κ = 75°, rake angle γ = 0°. Inserts are made of tungsten carbide quality K20, the following characteristics (l = IC = 12.7 mm; s = 3.18 mm; b_s = 1.4 mm; b_ε = 1.4 mm).

Measurement of cutting temperature was performed using the measuring acquisition system shown in Fig 3. The central part of the system is virtual instrumentation.

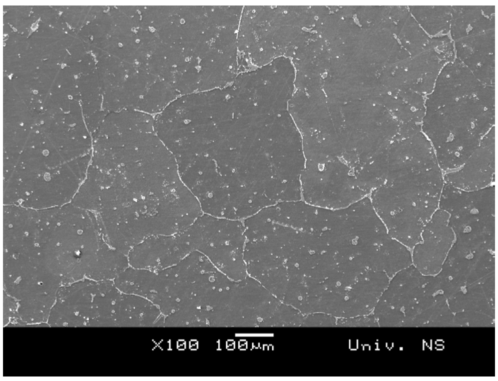

Fig. 2 Microstructure of tested aluminum alloy

Table 1 Chemical composition of the alloy 7075

Alloy designation	Basic element	Zn	Mg	Cu	Cr	Fe	Si	Mn	Ti
7075	Al	5.8	2.52	1.65	0.2	0.18	0.1	0.025	0.025

In the case of milling, unlike turning, there are problems of transmitting the signal from the tool to the measuring instrument. Due to the fact that the milling tool moves in a circular motion during the process, it is not possible to directly manage the thermocouple wire directly to the measuring instrument. Thermocouple wire connects to copper rings, which together with graphite brushes provide sliding contact. Contact with copper rings is provided by springs. Thermovoltage occurring when measuring temperature between 10 to 50 mV, so small losses also mean large measurement errors. The thermocouple is made of Ni and CrNi wire with diameter of 0.1 mm. In the high-temperature zone, the wires were insulated using a ceramic tube of 0.9 mm in diameter, Fig. 4. The length of the tube was about 10 mm, and the insulation was PVC.

Apart of the measurement and acquisition system, temperature measurement was also performed by the ThermoPro TP8S thermal camera, which served as another verification of reliable temperature measurement. For the purposes of this research, i.e. measuring the roughness of the machined surface, it was used the device called „MarSurf PS1". The maximum measuring range is 350 μm (from -200 μm to + 150 μm). This device also meets the standards of the International Organization for Standardization DIN EN ISO 3.274.

The factor variation is performed at 5 level values, so that each mean value between adjacent levels of the geometric mean of these values. The selected levels of factors are shown in Table 2.

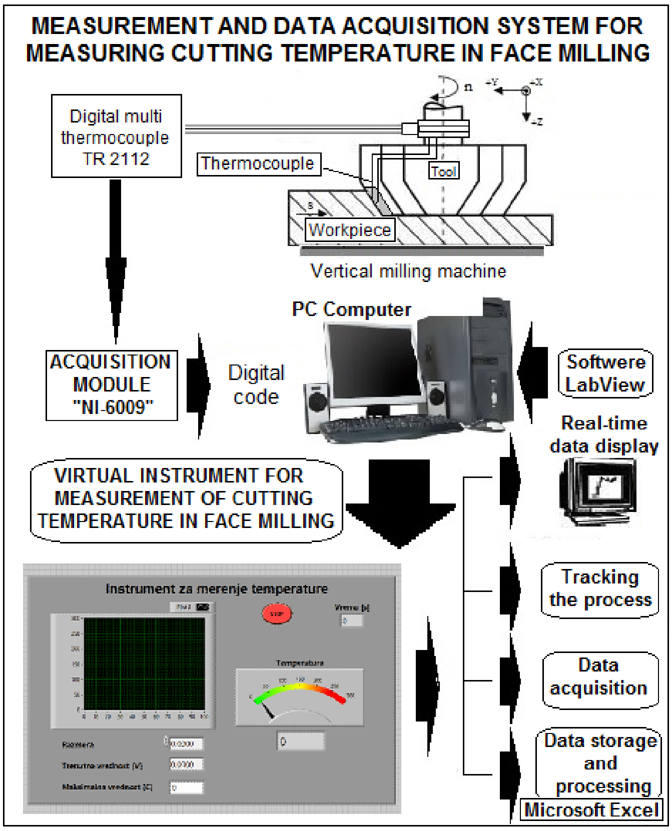

Fig. 3 Scheme of the measurement in face milling process

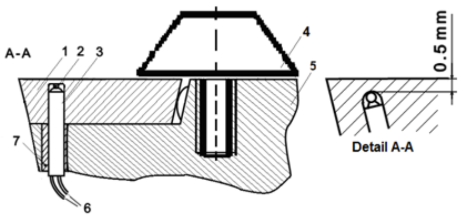

Fig. 4 Prepared cutting insert with thermocouple installed in the body of the milling head

1 – polygonal inserts, 2 – welded top of the thermocouple, 3 – ceramic tube, 4 – a screw that secures the insert, 5 – tool body, 6 – thermocouple PVC insulated, 7 – glue

Table 2 Levels of the experimental parameters for face milling

Levels (Functions of affiliation)	Cutting speed v (m/min)	Cutting speed v (m/s)	Feed to the tooth s_1 (mm/t)	Depth of cut a (mm)	Spindle speed n (min^{-1})
Highest +1.41	351.86	5.864	0.223	2.6	1120
High +1	282.74	4.712	0.177	1.72	900
Medium 0	223.05	3.717	0.141	1.14	710
Low -1	175.93	2.932	0.112	0.75	560
Lowest -1.41	141.37	2.356	0.089	0.5	450

4. Modeling using artificial intelligence methods

The realization of the model using artificial intelligence-based tools was done by using programs that have artificial neural networks, fuzzy logic (mamdani model) and genetic algorithms in their structure. Experimental data with a set of 21 experiments shown in the Table 3 were used to train these systems.

Table 4 shows the experimental data that were used for the test for further analysis of the models obtained.

Table 3 A plan of experimental testing with measured values for the process of training models based on artificial intelligence during face milling

No.	Factor			Measured values	
	v (m/s)	s_1 (mm/t)	a (mm)	Q (°C)	R_a (μm)
1	2.93	0.112	0.75	46	1.074
2	4.71	0.112	0.75	52	1.081
3	2.93	0.177	0.75	53	1.743
4	4.71	0.177	0.75	56	1.645
5	2.93	0.112	1.72	60	1.058
6	4.71	0.112	1.72	67	1.023
7	2.93	0.177	1.72	70	1.898
8	4.71	0.177	1.72	77	1.734
9	3.71	0.141	1.14	60	1.205
10	2.35	0.141	1.14	54	1.133
11	5.86	0.141	1.14	65	1.244
12	3.71	0.089	1.14	55	0.995
13	3.71	0.223	1.14	66	2.522
14	3.71	0.141	0.5	47	1.242
15	3.71	0.141	2.6	76.5	1.229
16	2.35	0.089	0.5	51	0.915
17	2.35	0.223	2.6	108	1.705
18	3.71	0.223	0.5	66	2.023
19	5.86	0.089	2.6	98	0.969
20	5.86	0.141	0.5	66	1.258
21	5.86	0.223	1.14	94	1.94

Table 4 Experimental data for testing the artificial intelligence model

No.	Factor			Measured values	
	v (m/s)	s_1 (mm/t)	a (mm)	Q (°C)	R_a (μm)
1	3.71	0.141	0.75	51	1.222
2	3.71	0.141	1.72	69	1.28
3	3.71	0.112	1.14	55	1.037
4	3.71	0.177	1.14	62	1.583
5	2.93	0.141	1.14	57	1.263
6	4.71	0.141	1.14	60	1.734

4.1 Neural network-based model

Training and testing are the most important features of a neural network (NN) which at the same time determine the characteristics of NN. The training will determine whether the neural network can provide the expected response or not. If that is not possible, NN will be trained again. The basic architecture of the artificial neural network consists of an input function, which can be in the form of binary, continuous or normalized data [36].

The distribution of data used for network training, validation or testing was as follows: 70 % of the data is training, 15 % data for validation, and 15 % for test data. A two-layer NN with sigmoid transfer function in hidden layers and linear transfer function in output layer (fit net) can arbitrarily incorporate multidimensional mapping problems, regarding consistent data and sufficient neurons in its hidden layer. The used NN has one hidden layer with 10 neurons. The network is trained with Levenberg-Markuard's return propagation algorithm (trainlm). This algorithm usually requires more memory, but less time. Cutting speed v (m/s), the feed per tooth s_1 (mm/t) and the cutting depth a (mm) are used as input data. These input data are grouped into one whole that is indicated $IN = (v, s_1, a)$. Output data are Q and R_a are not grouped, but a new network is created for each one individually. Due to that, models that were made were type 3-1, three inputs and one output, Fig. 5.

Fig. 6 shows a regression diagram in the neural network training process, where the goal is to set the value of the regression coefficient to be close to 1, the regression line should be at an angle of 45°, while most of the data from which the network is trained with should be along the line of regression.

When the network training is completed, simulation of the neural network can be performed. It is necessary to define inputs (*TestIn*), which are created on the base of Table 4, and based on those inputs to perform simulation and get new generated output process characteristics (*Test_outputs*).

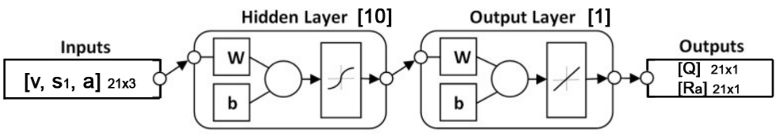

Fig. 5 Model of formed neural networks

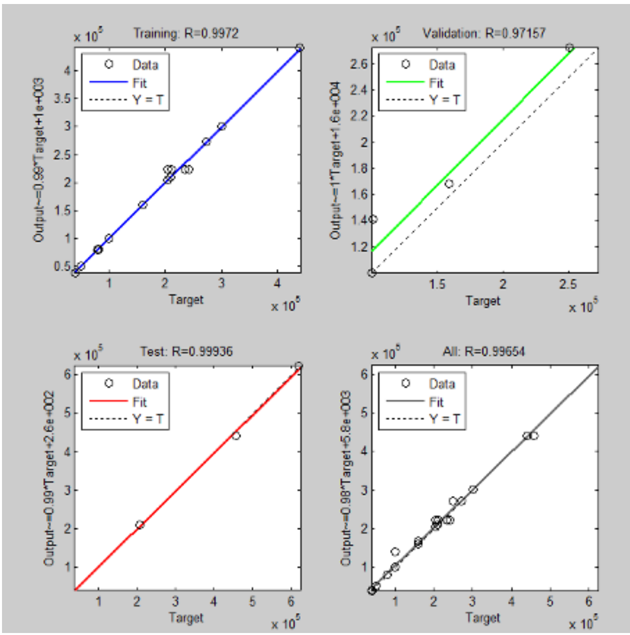

Fig. 6 Diagram of regression in the process of training a neural network

4.2 Fuzzy logic-based model

Implementation of the model based on fuzzy logic of the Mamdani type consists of several steps, where it is necessary to give a contribution in terms of editing membership functions and appropriate rules. On these bases, the fuzzy inference system comes to an editing, and there is a graphical representation of the appropriate solutions. Mamdani type implies that the language values of the output variable are regular fuzzy sets, where it is necessary to define the number of inputs, the names of the input and output variables. As with the neural network, there are three input variables (v, s_1, a) and the two output variables (Q, R_a) in face milling.

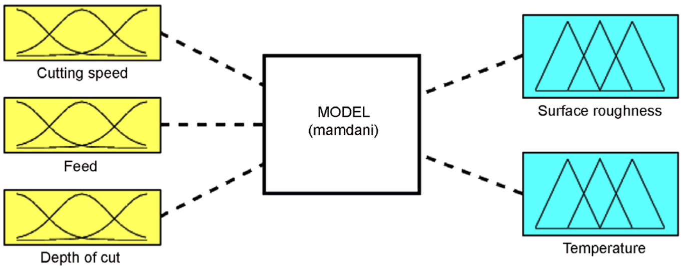

Fig. 7 Editor of fuzzy inference system

Editor of membership function enables the display and modification of all membership functions, input and output variables for the entire fuzzy inference system, Fig 7.

For the set problem, the Gaussian (gaussmf) membership function for each variable is defined. Gaussian membership function is the function most commonly used in modelling by using the fuzzy inference system [26, 27]. This symmetric Gaussian function depends on two parameters σ and C that need to be defined in the process of modeling, Eq. 1.

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

After accepting the rules comprehensible to the program package, that is, the highest value of the input parameter is represented numerically +1.41 written in an attribute form with *Highest*, respectively: +1 with *High*, 0 with *Medium*, -1 with *Low* and -1.41 with *Lowest* defining appropriate fuzzy set is performed.

The rules are defined so that the data that define the cutting temperature are divided into 6 fuzzy subsets labelled (A, B, C, D, E, F) that group the approximate output values arranged by the Gaussian distribution. For the second output process characteristic, 9 fuzzy sets (A, B, C, D, E, F, G, H, I) are defined according to the same principle.

Accordingly, the final rule understandable for fuzzy logic is: if *speed is* lower and *feed* is lower and *depth* is lower, then surface roughness in the set C, this is the first order. This way, the other rules, all 21 of them, are defined, Table 5.

Table 5 The modified table with corresponding subsets

No.	Factor			Measured values	
	v (m/s)	s_1 (mm/t)	*a* (mm)	*Q* (°C)	R_a (µm)
1	-1	-1	-1	A	C
2	1	-1	-1	B	D
3	-1	1	-1	B	G
4	1	1	-1	B	F
5	-1	-1	1	C	C
6	1	-1	1	D	C
7	-1	1	1	D	H
8	1	1	1	E	G
9	0	0	0	C	E
10	-1.41	0	0	B	D
11	1.41	0	0	D	E
12	0	-1.41	0	B	B
13	0	1.41	0	D	I
14	0	0	-1.41	A	E
15	0	0	1.41	E	E
16	-1.41	-1.41	-1.41	B	A
17	-1.41	1.41	1.41	F	G
18	0	1.41	-1.41	D	H
19	1.41	-1.41	1.41	F	B
20	1.41	0	-1.41	D	E
21	1.41	1.41	0	F	H

4.3 Genetic algorithm-based model

Predefined second-order model, obtained based on a previous regression analysis based on the design of the experiment, was used to model the function of Q (cutting temperature) and Ra (arithmetic mean roughness):

$$Q = C_1 \cdot v^{x_1} \cdot {s_1}^{x_2} \cdot a^{x_3} \tag{2}$$

$$R_a = C_2 \cdot v^{x_4} \cdot {s_1}^{x_5} \cdot a^{x_6} \tag{3}$$

When determining the appropriate shape of the model, the genetic algorithm method starts from the initial random population $P(t)$. Population $P(t)$ is composed of organisms. Each organism is one of the possible solutions to the problem and consists of real constants (gens): C_1, x_1, x_2, x_3, C_2, x_4, x_5, x_6.

Based on already performed examinations and calculations based on regression analysis, as well as due to faster detection of the optimal solution, the limits in the search area have been introduced. Thus, the positioning of possible solutions, the coefficients for determining tool stability, are localized to: $60 \leq C_1 \leq 80$; $0.1 \leq x_1 \leq 0.5$; $0.1 \leq x_2 \leq 0.5$; $0.1 \leq x_3 \leq 0.5$.

After generating the initial population, the iterative procedure of selection, recombination (crossover) and mutation is carried out until the convergence criterion is satisfied, Fig. 8.

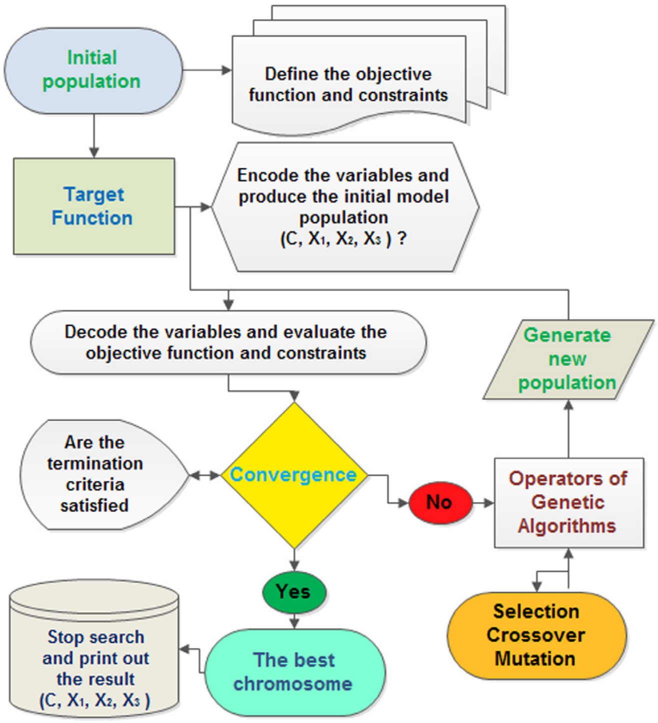

Fig. 8 Principle of the genetic algorithm

Determining the interactions that occur among different GA parameters has a direct impact on the quality of the solution and keeping parameters values *balanced* improves the solution of the GA. For machining process modeling, GA with the following parameters was used: population size 150, crossover rate 0.8, mutation rate 0.03 and number of generations 1000.

The only difference between modelling the function for cutting temperature and arithmetic mean roughness is precisely in the values of the search area limits. Thus, the determination of the coefficients that are represented in the equation for the arithmetic mean roughness are set to the constraints in terms of the limits: $10 \leq C_2 \leq 20$; $-0.5 \leq x_4 \leq 0.5$; $1 \leq x_5 \leq 1.5$; $-0.5 \leq x_6 \leq 0.5$.

After generating the optimal constants through the genetic algorithms, the Eqs. 4 and 5 have the final form:

$$\mathrm{Q} = 72.551 \cdot v^{0.305} \cdot {s_1}^{0.297} \cdot a^{0.311} \tag{4}$$

$$R_\mathrm{a} = 12.337 \cdot v^{-0.059} \cdot {s_1}^{1.088} \cdot a^{-0.018} \tag{5}$$

5. Results and discussion

The quantitative predictive potential E, the Eq. 6 is evaluated due to percentage of deviation between the obtained values (using the corresponding model) and the expected (experimental) values for the temperature in the cutting zone Q and the surface roughness R_a for the data on the basis of which the training of corresponding models of artificial intelligence was performed. The results presented are given in Table 6 and Table 7. The verification of the accuracy of these models was performed on the basis of 6 additional experiments performed according to the plan given in the second part of Tables 6 and 7.

Based on the average percentage error, it can be concluded that in both output characteristics of the process for the data used in the training of the corresponding model, this percentage error does not exceed 10 %. The situation is similar with test data where models used for cutting temperatures Q are also below 10 %, while in arithmetic main roughness R_a obtains a maximum deviation of 14 % using an artificial neural network-based model. Comparing all three models, it is concluded that looking at both output characteristics of the process, the smallest error was made by the model based on fuzzy logic. Consequently, it is recommended that the knowledge base, based on artificial intelligence is recommend built into the appropriate process systems.

$$E = \frac{|Y_{i\ \mathrm{mod}} - Y_{i\ \exp}|}{Y_{i\ \exp}} * 100\ \%;\ i = 1 \dots n,\ \ Y_i = \ \theta_i;\ R_{a_i} \tag{6}$$

Table 6 Comparison of NN, FL, and GA predictive models for cutting temperature Q

	No.	$\theta_{Exp.}$ (°C)	$\theta_{N.N.}$ (°C)	E (%)	$\theta_{F.L.}$ (°C)	E (%)	$\theta_{G.A.}$ (C°)	E (%)
Training data	1	46	48.80	6.1	48.82	6.13	48.06	4.48
	2	52	52.32	0.61	54.17	4.17	55.55	6.82
	3	53	54.24	2.35	54.16	2.18	55.06	3.88
	4	56	56.67	1.19	54.07	3.44	63.64	13.64
	5	60	60.03	0.05	62.29	3.81	62.22	3.69
	6	67	67.13	0.19	67.50	0.74	71.91	7.33
	7	70	69.94	0.09	67.50	3.58	71.27	1.82
	8	77	77.15	0.19	75.98	1.33	82.38	6.98
	9	60	60.64	1.06	61.42	2.38	62.99	4.99
	10	54	53.87	0.24	53.95	0.09	54.81	1.49
	11	65	64.85	0.23	62.03	4.57	72.42	11.41
	12	55	55.16	0.29	53.95	1.91	54.95	0.09
	13	66	79.13	19.89	67.50	2.27	72.18	9.37
	14	47	45.03	4.19	48.94	4.12	48.75	3.73
	15	76.5	75.65	1.11	76.00	0.65	81.41	6.42
	16	51	51.26	0.51	53.48	4.86	36.99	27.46
	17	108	117.68	8.96	101.00	6.48	81.16	24.85
	18	66	59.50	9.84	67.50	2.27	55.86	15.36
	19	98	97.97	0.03	101.00	3.06	81.63	16.69
	20	66	65.99	0.01	67.49	2.26	56.05	15.08
	21	94	93.92	0.08	100.96	7.41	82.98	11.72
		Average error ⇒		2.72		3.22		9.39
Testing data	1	51	48.84	4.23	48.058	5.77	55.30	8.44
	2	69	65.53	5.03	64.94	5.88	71.59	3.76
	3	55	54.98	0.04	55.01	0.02	58.83	6.97
	4	62	54.88	11.48	56.81	8.36	67.39	8.71
	5	57	55.03	3.45	54.54	4.32	58.62	2.84
	6	60	53.96	10.06	56.29	6.18	67.75	12.92
		Average error ⇒		5.72		5.09		7.27

Table 7 Comparison of NN, FL, and GA predictive models for arithmetic mean roughness R_a

	No.	$R_{a\ Exp.}$ (μm)	$R_{a\ N.N.}$ (μm)	E (%)	$R_{a\ F.L.}$ (μm)	E (%)	$R_{a\ G.A.}$ (μm)	E (%)
Training data	1	1.074	1.071	0.24	1.048	2.38	1.075	0.11
	2	1.081	1.075	0.53	1.129	4.53	1.045	3.29
	3	1.743	1.418	18.63	1.707	2.04	1.769	1.49
	4	1.645	1.643	0.09	1.517	7.8	1.720	4.56
	5	1.058	0.617	41.66	1.066	0.74	1.059	0.11
	6	1.023	1.313	28.33	1.057	3.36	1.029	0.68
	7	1.898	1.751	7.74	2.002	5.48	1.742	8.18
	8	1.734	1.733	0.08	1.722	0.68	1.695	2.27
	9	1.205	1.205	0.02	1.244	3.2	1.352	12.19
	10	1.133	1.135	0.21	1.141	0.72	1.389	22.58
	11	1.244	1.245	0.1	1.241	0.26	1.316	5.78
	12	0.995	0.999	0.37	1.003	0.84	0.819	17.64
	13	2.522	2.488	1.35	2.552	1.19	2.226	11.73
	14	1.242	1.237	0.37	1.240	0.14	1.372	10.47
	15	1.229	1.218	0.88	1.240	0.9	1.332	8.38
	16	0.915	0.909	0.68	0.940	2.77	0.850	7.10
	17	1.705	1.707	0.12	1.725	1.17	2.253	32.15
	18	2.023	2.017	0.3	2.011	0.61	2.259	11.68
	19	0.969	1.029	6.21	0.996	2.79	0.786	18.89
	20	1.258	1.259	0.08	1.240	1.41	1.336	6.17
	21	1.94	1.944	0.19	2.011	3.64	2.167	11.69
		Average error ⇒		5.15		2.22		9.39
Testing data	1	1.222	1.253	2.51	1.241	1.50	1.362	11.47
	2	1.28	1.022	20.12	1.328	3.73	1.342	4.84
	3	1.037	0.911	12.12	1.053	1.59	1.052	1.48
	4	1.583	1.763	11.39	1.611	1.79	1.731	9.37
	5	1.263	1.124	10.99	1.143	9.54	1.371	8.54
	6	1.734	1.240	28.46	1.257	27.51	1.333	8.02
		Average error ⇒		14.26		7.61		7.29

Another analysis of the accuracy of the corresponding models was performed based on simple linear regression. Figs. 9 and 10 show diagrams of actual and predicted values as well as the calculated coefficient of determination for each proposed model. Based on the analysis of the coefficient of determination in defining the most accurate model for predicting the cutting temperature Q, the following can be stated: the fuzzy logic model gave the best match of actual and predicted values (R^2 = 0.982), next the neural network model (R^2 = 0.945), and finally the most unfavourable prediction comes from a model based on GA. In this case, the first two models are acceptable for further implementation in process systems, while the GA model should be avoided.

Fig. 10 also shows an analysis of deviation of the values of the arithmetic mean roughness, where it is concluded that the fuzzy logic model gives a completely correct representation of the actual and predicted values with a very high coefficient of determination. The values for the other two models based on the membership interval belong to the domain of good correlation.

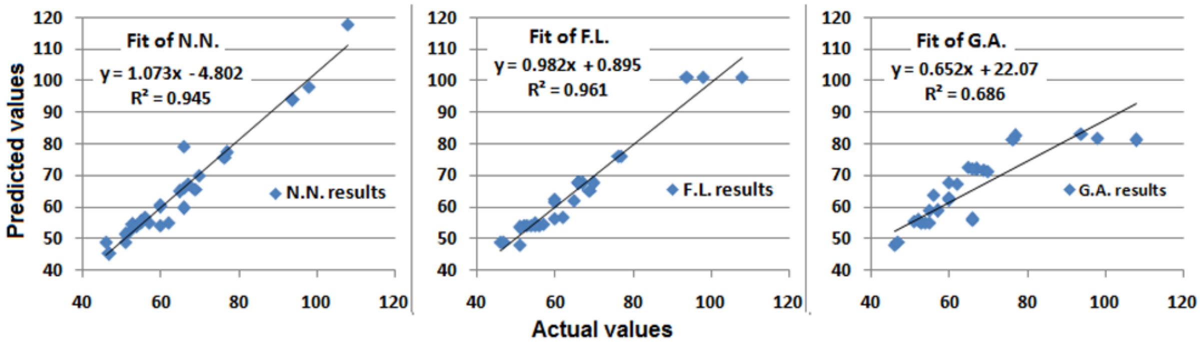

Fig. 9 Diagram of actual and predicted values for cutting temperature

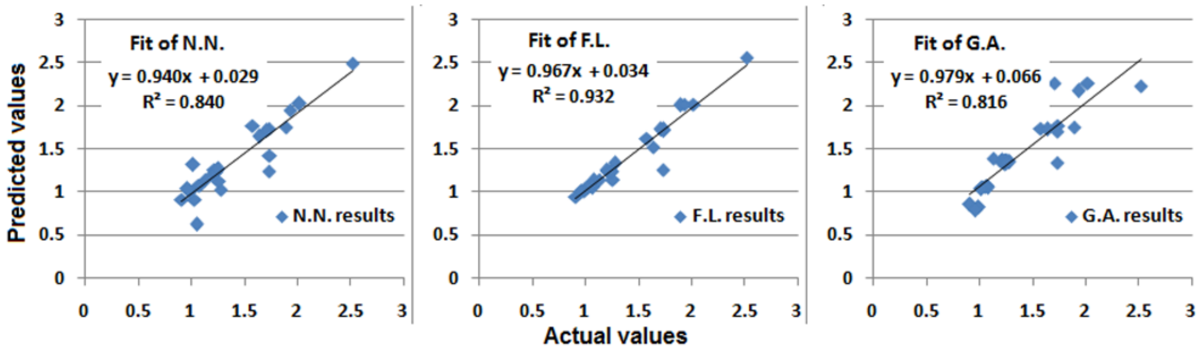

Fig. 10 Diagram of the actual and predicted values for the arithmetic mean roughness

Based on the overall analysis, taking into account the values based on the quantitative predictive potential E as well as the coefficient of determination R^2, it is concluded that the models based on fuzzy logic are the most suitable for further use.

6. Conclusion

By modeling the machinability functions of the milling process, i.e., the machining conditions and the output characteristics of the process, the conditions for a predict control and optimize process parameters have been created. The modeling process was performed using artificial intelligence based methods. Models were realized by artificial neural networks, fuzzy logic and genetic algorithms with the analysis of the accuracy. The obtained models for each machinability function were analyzed and on the basis of least error of deviation, the best model is proposed. An analysis was also performed in terms of the values of the coefficient of determination for each individual model as a function of the corresponding characteristics of the face milling process. The verification of the accuracy of the model was performed on the basis of additional experiments, which were not used in training phase. Based on a comprehensive analysis, it can be concluded that the application of the Fuzzy logic is the most adequate in the examined process. A further recommendation would be in the application of artificial neural networks in the first place, and then genetic algorithms in the second place.

The successful theoretical and experimental research has demonstrated the applicability of new modeling methods to milling processes. Also, models developed using artificial intelligence tools have a potential application in the industry. Consequently, the results of this research have their significance in that view, i.e., they can be integrated into manufacturing systems within which the tools of the integrated memory for the knowledge base are represented.

References

[1] Klancnik, S., Begic-Hajdarevic, D., Paulic, M., Ficko, M., Cekic, A., Husic, M.C. (2015). Prediction of laser cut quality for tungsten alloy using the neural network method, *Strojniški Vestnik – Journal of Mechanical Engineering*, Vol. 61, No. 12, 714-720, doi: 10.5545/sv-jme.2015.2717.

[2] Fulemová, J., Řehoř, J. (2015). Influence of form factor of the cutting edge on tool life during finishing milling, *Procedia Engineering*, Vol. 100, 682-688, doi: 10.1016/j.proeng.2015.01.420.

[3] Simunovic, G., Simunovic, K., Saric, T. (2013). Modelling and simulation of surface roughness in face milling, *International Journal of Simulation Modelling*, Vol. 12, No. 3, 141-153, doi: 10.2507/IJSIMM12(3)1.219.

[4] Perez, C.J.L. (2002). Surface roughness modeling considering uncertainty in measurements, *International Journal of Production Research*, Vol. 40, No. 10, 2245-2268, doi: 10.1080/00207540210125489.

[5] Ferreira, R., Rehor, J., Lauro, H.C., Carou , D., Davim , J.P. (2016). Analysis of the hard turning of AISI H13 steel with ceramic tools based on tool geometry: surface roughness, tool wear and their relation, *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 38, 2413-2420, doi: 10.1007/s40430-016-0504-z.

[6] Efkolidis, N., Hernández, C.G., Talón, J.L.H., Kyratsis, P. (2018). Modelling and prediction of thrust force and torque in drilling operations of Al7075 using ANN and RSM methodologies, *Strojniški Vestnik – Journal of Mechanical Engineering*, Vol. 64, No. 6, 351-361, doi: 10.5545/sv-jme.2017.5188.

[7] Hrelja, M., Klancnik, S., Balic, J., Brezocnik, M. (2014). Modelling of a turning process using the gravitational search algorithm, *International Journal of Simulation Modelling*, Vol. 13, No. 1, 30-41, doi: 10.2507/IJSIMM13(1)3.248.

[8] Ojstersek, R., Lalic, D., Buchmeister, B. (2019). A new method for mathematical and simulation modelling interactivity: A case study in flexible job shop scheduling, *Advances in Production Engineering & Management*, Vol. 14, No. 4, 435-448, doi: 10.14743/apem2019.4.339.
[9] Sekulic, M., Pejic, V., Brezocnik, M., Gostimirović, M., Hadzistevic, M. (2018). Prediction of surface roughness in the ball-end milling process using response surface methodology, genetic algorithms, and grey wolf optimizer algorithm, *Advances in Production Engineering & Management*, Vol. 13, No. 1, 18-30, doi: 10.14743/apem2018.1.270.
[10] Meireles, M.R.G., Almeida, P.E.M., Simoes, M.G. (2003). A comprehensive review for industrial applicability of artificial neural networks, *IEEE Transactions on Industrial Electronics*, Vol. 50, No. 3, 585-601, doi: 10.1109/TIE.2003.812470.
[11] Balic, J., Korosec, M. (2002). Intelligent tool path generation for milling of free surfaces using neural networks, *International Journal of Machine Tools and Manufacture*, Vol. 42, No. 10, 1171-1179, doi: 10.1016/S0890-6955(02)00045-7.
[12] Azouzi, R., Gullot, M. (1997). On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion, *International Journal of Machine Tools and Manufacturing*, Vol. 37, No. 9, 1201-1217, doi: 10.1016/S0890-6955(97)00013-8.
[13] Singh, A.K., Panda, S.S., Chakraborty, D., Pal, S.K. (2006). Predicting drill wear using an artificial neural network, *The International Journal of Advanced Manufacturing Technology*, Vol. 28, No. 5, 456-462, doi: 10.1007/s00170-004-2376-0.
[14] Zuperl, U., Cus, F., Zawada-Tomkiewicz, A., Stępień, K. (2020). Neuro-mechanistic model for cutting force prediction in helical end milling of metal materials layered in multiple directions, *Advances in Production Engineering & Management*, Vol. 15, No. 1, 5-17, doi: 10.14743/apem2020.1.345.
[15] Savković, B., Kovac, P., Gerić, K., Sekulić, M., Rokosz, K. (2013). Application of neural network for determination of cutting force changes versus instantaneous angle in face milling, *Journal of Production Engineering*, Vol. 16, No. 2, 1-4.
[16] Lin, S.C., Ting, C.J. (1996). Drill wear monitoring using neural networks, *International Journal of Machine Tools and Manufacture*, Vol. 36, No. 4, 465-475, doi: 10.1016/0890-6955(95)00059-3.
[17] Liu, T.I., Chen, W.Y., Anantharaman, K.S. (1998). Inteligent detection of drill wear, *Mechanical Systems and Signal Procesing*, Vol. 12, No. 6, 863-873, doi: 10.1006/mssp.1998.0165.
[18] Zuperl, U., Čuš, F., Kiker, E. (2006). Intelligent adaptive cutting force control in end-milling, *Tehnički Vjesnik – Technical Gazzete,* Vol. 13, No. 1-2, 15-22.
[19] Zadeh, L.A. (1965). Fuzzy sets, *Information and Control*, Vol. 8, No. 3, 338-353, doi: 10.1016/S0019-9958(65)90241-X.
[20] Sivarao, S., Brevern, P., El-Tayeb, N.S.M., Vengkatesh, V.C. (2009). GUI based Mamdani fuzzy Inference system modeling to predict surface roughness in laser machining, *International Journal of Electrical & Computer Sciences IJECS-IJENS*, Vol. 9, No. 9, 281-288.
[21] Rajasekaran, T., Palanikumar, K., Vinayagam, B.K. (2011). Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool, *Production Engineering*, Vol. 5, No. 2, 191-199, doi: 10.1007/s11740-011-0297-y.
[22] Savković, B., Kovač, P., Rodic, D., Gostimirovic, M., Pucovski, V., Holešovský, F. (2014). Application of ANFIS for modeling and prediction of the surface roughness for steel dificult to machining, In: *Proceedings of 8st International Scientific Conference on Mechanical Engineering-COMEC*, Faculty of Mechanical and Industrial Engineering, UCLV, Cuba, 1-11.
[23] Lo, S.-P. (2003). An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling, *Journal of Materials Processing Technology*, Vol. 142, No. 3, 665-675, doi: 10.1016/S0924-0136(03)00687-3.
[24] Ho, S.-Y., Lee, K.-C., Chen, S.-S., Ho, S.-J. (2002). Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system, *International Journal of Machine Tools and Manufacture*, Vol. 42, No. 13, 1441-1446, doi: 10.1016/S0890-6955(02)00078-0.
[25] Hany, F. (2003). Handwriting digit reorganization with fuzzy logic, *Jurnal Teknik Elektro*, Vol. 3, No. 2, 84-87.
[26] Kovac, P., Rodic, D., Pucovsky, V., Savkovic, B., Gostimirovic, M. (2013). Application of fuzzy logic and regression analysis for modeling surface roughness in face milling, *Journal of Intelligent Manufacturing*, Vol. 24, No. 4, 755-762, doi: 10.1007/s10845-012-0623-z.
[27] Kovac, P., Rodic, D., Pucovsky, V., Savkovic, B., Gostimirovic, M. (2014). Multi-output fuzzy inference system for modeling cutting temperature and tool life in face milling, *Journal of Mechanical Science and Technology*, Vol. 28, No. 10, 4247-4256, doi: 10.1007/s12206-014-0938-0.
[28] Balic, J., Kovacic, M., Vaupotic, B. (2006). Intelligent programming of CNC turning operations using genetic algorithm, *Journal of Intelligent Manufacturing*, Vol. 17, No. 3, 331-340, doi: 10.1007/s10845-005-0001-1.
[29] Batish, A., Bhattacharya, A., Kaur, M, Cheema, M.S. (2014). Hard turning: Parametric optimization using genetic algorithm for rough/finish machining and study of surface morphology, *Journal of Mechanical Science and Technology*, Vol. 28, No. 5, 1629-1640, doi: 10.1007/s12206-014-0308-y.
[30] Dorlin, T., Fromentin, G., Costes, J.-P. (2016). Generalised cutting force model including contact radius effect for turning operations on Ti6Al4V titanium alloy, *International Journal of Advanced Manufacturing Technology*, Vol. 86, No. 9-12, 3297-3313, doi: 10.1007/s00170-016-8422-x.
[31] Santos, M.C., Machado, A.R., Barrozo, M.A.S., Jackson, M. J., Ezugwu, E.O. (2015). Multi-objective optimization of cutting conditions when turning aluminum alloys (1350-O and 7075 T6 grades) using genetic algorithm, *Inter-*

national Journal of Advanced Manufacturing Technology, Vol. 76, No. 5-8, 1123-1138, doi: 10.1007/s00170-014-6314-5.

[32] Sivasakthivel, P.S., Sudhakaran, R. (2013). Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm, *The International Journal of Advanced Manufacturing Technology*, Vol. 67, No. 9, 2313-2323, doi: 10.1007/s00170-012-4652-8.

[33] Lukic, D., Milosevic, M., Antic, A., Borojevic, S., Ficko, M. (2017). Multi-criteria selection of manufacturing processes in the conceptual process planning, *Advances in Production Engineering & Management*, Vol. 12, No. 2, 151-162, doi: 10.14743/apem2017.2.247.

[34] Borojević, S., Lukić, D., Milošević, M., Vukman, J., Kramar, D. (2018). Optimization of process parameters for machining of Al 7075 thin-walled structures, *Advances in Production Engineering & Management*, Vol. 13, No. 2, 121-232, doi: 10.14743/apem2018.2.278.

[35] Stojanović, B., Ivanović, L. (2015). Application of aluminium hybrid composites in automotive industry, *Tehnički vjesnik – Technical Gazette*, Vol. 22, No. 1, 247-251, doi: 10.17559/TV-20130905094303.

[36] Kovač, P., Rodić, D., Pucovski, V., Mankova, I., Savkovic, B ., Gostimirović, M. (2012). A review of artificial inteligence approaches applied in inteligent processes, *Journal of Production Engineering*, Vol. 15, No. 1, 1-6.